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Colombo, Sergio; Christie, Mike; Hanley, Nick

Published in:
Ecological Economics

DOI:
10.1016/j.ecolecon.2013.08.016

Publication date:
2013

Citation for published version (APA):
Colombo, S., Christie, M., & Hanley, N. (2013). What are the consequences of ignoring attributes in choice experiments? Implications for ecosystem service valuation. *Ecological Economics*, *96*, 25-35. https://doi.org/10.1016/j.ecolecon.2013.08.016

Ecological Economics 96 (2013) 25–35

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Methodological and Ideological Options

What are the consequences of ignoring attributes in choice experiments? Implications for ecosystem service valuation

Sergio Colombo [a], Michael Christie [b,*], Nick Hanley [c]

[a] Department of Agricultural Economics, IFAPA, Junta de Andalusia, Spain
[b] School of Management and Business, Aberystwyth University, Llanbadarn Campus, Aberystwyth, Ceredigion SY23 3AL, Wales, UK
[c] Economics Division, University of Stirling, Stirling FK9 4LA, Scotland, UK

ARTICLE INFO

Article history:
Received 18 December 2012
Received in revised form 10 May 2013
Accepted 23 August 2013
Available online xxxx

Keywords:
Choice experiments
Attribute non-attendance
Biodiversity values
Ecosystem service values
Stated preference methods

ABSTRACT

This paper investigates the sensitivity of choice experiment values 3AL for ecosystem services to 'attribute non-attendance'. We consider three cases of attendance, namely that people may always, sometimes, or never pay attention to a given attribute in making their choices. This allows a series of models to be estimated which addresses the following questions: To what extent do respondents ignore attributes in choice experiments? What is the impact of alternative strategies for dealing with attribute non-attendance? Can respondents reliably self-report non-attendance? Do respondents partially attend to attributes, and what are the implications of this? Our results show that allowing for the instance of 'sometimes attending' to attributes in making choices offers advantages over methods employed thus far in the literature.

1. Introduction

Over the past few decades, non-market valuation techniques have increasingly been utilised in policy design and appraisal to assess the economic value of environmental goods and services. Amongst the valuation methods developed by economists, the choice experiment (CE) approach has proved to be one of the most adaptable and widely-applicable (Adamowicz et al., 1997; Carson and Louviere, 2011); although their use still excites much controversy (Hanley and Barbier, 2009). The attraction of CE lies in the ability of the researcher to estimate values for changes in a number of attributes (for example, a number of ecosystem services supplied by a biome), as well as compensating or equivalent surplus measures of multiple changes in attribute levels. The CE method is based on a fundamental assumptions that people are willing to make trade-offs between different levels of the included attributes in order to maximise utility, and that they 'pay attention' to all of these attributes in making their choices. However, since the work of Hensher et al. (2005), evidence is emerging that (i) at least some respondents in CE are not willing to make trade-offs between certain attributes; and (ii) that not all attributes are considered by all respondents in making their choices. This raises a concern that choices violate the continuity axiom which underlies the conventional framework for individual choice, and thus that the method cannot be relied on to produce reliable estimates of economic value.

In this paper, we use a CE focussed on a range of ecosystem services associated with UK habitats to test for the occurrence of attribute non-attendance (AN-A) and to examine the effects that allowing for non-attendance econometrically has for preference estimation and willingness to pay calculations. Unlike previous studies, respondents are allowed to select an option that they 'sometimes considered' an attribute in choosing a policy option, rather than just that they 'always considered' or 'never considered' the attribute. Data is collected in a valuation workshop setting (Christie et al., 2006), which we argue should reduce the likelihood of respondents ignoring attributes in their choices as a way of reducing the difficulty of choosing (that is, as a choice heuristic). Finding evidence of attribute non-attendance in such participatory contexts poses greater challenges to the standard compensatory choice paradigm and to the values derived from choice experiments, since it is more likely to reflect an unwillingness to make trade-offs, rather than mental difficulties in making trade-offs.

To preview our main results, we find that allowing people to state that they 'sometimes' ignore an attribute has significant effects on both estimated preferences and welfare measures. Unlike some of the existing literature, we do not find that price is the most ignored attribute. Ignoring prices would be especially troublesome, since this undermines the calculation of willingness to pay.

2. Attribute Non-attendance in Choice Models: What Do We Know, and Why Does This Matter?

The standard approach to choice modelling is to assume that respondents' utility is determined by a utility function which is defined over a

* Corresponding author. Tel.: +44 1970 622217; fax: +44 1970 622409.
E-mail address: mec@aber.ac.uk (M. Christie).

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http://dx.doi.org/10.1016/j.ecolecon.2013.08.016

clearly defined set of attributes or characteristics of a good, one of which is its price. Most typically, a linear, additively separable form of the indirect utility function is used. The random utility perspective means that the researcher is only able to observe and thus model the deterministic aspects of behaviour. A key assumption is that individuals are willing and able to make trade-offs between the attributes of a good within the deterministic part of their utility function over the entire range of values that each attribute can take, as specified in the experimental design. Thus, there is always an additional amount of attribute X_1 that will compensate for a reduction in another, positively-valued attribute X_2 and keep the respondent on a given indifference curve. Whilst it is not necessary to assume that indifference curves between any two attributes are smooth, it is necessary that indifference curves are continuous. If this is not the case, then willingness to pay for some changes in attributes is not defined (Scarpa et al., 2009). The degree of attribute non-attendance and its causal factors are both critical to the derivation of economic value estimates from choice experiments.

Several researchers have looked for evidence to suggest that this assumption of compensatory preferences is untenable. Within the contingent valuation literature, one group of early studies considered evidence for lexicographic preferences (e.g., Rekola, 2003; Spash and Hanley, 1995). Lexicographic preferences imply that certain attributes or goods are always preferred to other goods or attributes, no matter what level they are supplied at. Lexicographic preferences are often taken to be incompatible with the derivation of WTP or WTA measures of value, since, for example, such preferences would not allow a reduction in environmental quality in exchange for an increase in income. Within choice modelling, evidence for non-compensatory preferences has followed a different tack, focussing on attribute non-attendance. Studies of this type include Hensher et al. (2005), Campbell et al. (2008) and Carlsson et al. (2010). Before reviewing the empirical findings of this work, we first consider the possible implications of different responses to non-attendance questions.

Consider a choice experiment where the researcher assumes that the deterministic portion of utility depends on three non-price attributes for a good, X_1, X_2 and X_3, and a price attribute, X_4. Choice tasks are constructed which combine these four attributes at various levels. Respondents are then asked whether they paid attention to all four attributes in making their choices. Four types of response are possible, with a range of implications for how the researcher can interpret the resultant choice data.

First, some individuals may state that they always pay attention to all of the attributes in making their choices. Such individuals are behaving according to the standard model of choice in the choice experiment approach. Second, people may state that they did not pay attention to X_1, or perhaps to X_1 and X_2, in making their choices. One interpretation of this is that they do not care about the levels of these attributes over the range specified in the design, and that the researcher was wrong in assuming this in her experimental design. In this case, a marginal utility of zero should be allocated for this respondent for this attribute in coding responses. If the individual says they paid no attention to X_4 (the price), then this is particularly serious, since it mitigates against the calculation of welfare measures for people who do not attend to this attribute (Hess et al., 2012; Scarpa et al., 2009). Such responses may imply that the researcher has done a bad job of constructing a credible payment scenario, or set price levels which are much too low. If many individuals do not care about X_1, then the parameter estimated for X_1 in the choice model should be statistically insignificant. Hess et al. (2012) consider this issue as a potential mixing-up of not caring about an attribute (and thus ignoring it in choices), and not caring about it very much: that is, mixing-up low with no utility being attached to an attribute.

An alternative interpretation is that respondents are ignoring X_1, and perhaps X_1 and X_2, as a way of simplifying their task in choosing between alternatives (Carlsson et al., 2010). Use of this boundedly-rational heuristic complicates matters for the researcher, since it does not signal that the individual places no value on X_1. Failing to allow for this motivation for ignoring X_1 will mean that welfare measures for changes in X_1 are biased downwards. Note that the respondent may state that they ignored an attribute despite the statistical evidence of their choices suggesting otherwise.

A third possible response is that an individual says that they only paid attention to one attribute (X_3) in choosing. Again, this makes possible a number of interpretations. It may signal that the individual has lexicographic preferences with respect to X_3, so that all bundles are ranked solely with regard to the amount of X_3 supplied. In such cases, WTP is undefined for this attribute (although see Rekola, 2003). Alternatively, this may suggest that the respondent uses X_3 to choose in order to simplify choices. This might be true of respondents who focus solely on the price attribute.

A final possible response is that the individual states that they 'sometimes' pay attention to X_3. This could suggest that X_3 becomes relevant to choice only when its level is within certain bounds. This would suggest use of a cut-offs model to analyse choice data (Bush et al., 2009); or that the statistical modelling of choice should take such “sometimes consider” responses into account in some other way. Allowing people to state that they “sometimes” consider an attribute, as well as 'always' or 'never' consider it would seem appropriate if this better describes how people choose. This is the approach followed in the experiment reported here. Before explaining its design, however, we first review the main findings that have been reported so far in the literature on attribute non-attendance (Lanscar and Louviere, 2006).

Hensher et al. (2005) was the first contribution to the CE literature on attribute non-attendance. In a study of commuters in Sydney, Australia, they show that allowing for the fact that some respondents stated that they did not pay attention to some attributes changed their estimates of the value of travel time savings. Campbell et al. (2008) applied choice modelling to the valuation of landscape attributes in Ireland which were affected by implementation of an agri-environment scheme. Respondents were asked whether they paid attention to all attributes in making their choices. Those who did were labelled as having ‘continuous’ preferences, and those who said they did not were labelled as having ‘discontinuous’ preferences. The authors found that 64% of the sample considered all attributes and 34% did not, but around one-fifth focussed on one attribute alone, and thus did not engage in any trade-offs. Price was the attribute which was least-attended to, and only two-thirds of respondents were willing to trade off at least one attribute against price. Campbell et al. found that explicitly accounting for attribute non-attendance in the choice model improved its statistical fit, and also reduced estimated WTP, although it did not change the ranking of attributes in terms of their implicit prices. They found that adjusting for relative scale differences (that is, differences in error variance) between continuous and discontinuous preferences was also effective. In a related paper, Campbell et al. (2011) use a latent class model to analyse attribute non-attendance in the same data set. Again, accounting for possible non-attendance reduced estimates of willingness to pay for landscape improvements, partly because of the high degree of non-attendance to price.

Carlsson et al. (2010) questioned respondents as to which attributes they took into account in choosing between the design of three different environmental policies in Sweden (policy on freshwater quality in lakes and streams; policies on the marine environment; and policies on air pollution). They found that around one-half of respondents claimed to ignore at least one attribute in choosing, and around one-third claimed to ignore at least two attributes. Price was the attribute most ignored according to these responses. One interesting feature of this work is that the authors find evidence that what people say about whether they ignore an attribute or not is not a very robust predictor of whether it statistically impacts on their choices. They interacted dummy variables for stated ignoring of an attribute with the level of this attribute, and found that the parameter on this interaction was insignificant, implying no significant difference in estimated preferences between those who say they ignore an attribute and those who do not make this claim.

So far, the studies described have involved asking respondents about which attributes they attended to at the end of the set of choice tasks. However, there is evidence which shows that respondents may attend to different attributes in different choice tasks, in the sequence of choices they face. Scarpa et al. (2010) and Meyerhoff and Liebe (2009) tested this by asking individuals about ignored attributes at the end of each choice task and comparing the results with the data resulting from asking the attendance at the end of the set of choice tasks. Both studies found advantages to monitoring attribute attendance at choice task level instead of at choice task sequence level, although the impacts on WTP are mixed. Scarpa et al. (2010) found an efficiency gains in term of the magnitude and reality of the estimated WTP at the choice task level, whereas Meyerhoff and Leibe (2009) found little difference in implicit prices according to how respondents' attribute non-attendance is classified.

In a behavioural context, it is difficult to explain why respondents focus on a specific attribute just in some choices. A possible reason is that respondents misunderstand the non-attendance question and declare that they have ignored an attribute when instead they have a low marginal utility for it. For instance, this may happen when respondents have a cost threshold and exclude the cost information of those alternatives which are outside their cost threshold. This may explain the inconsistencies observed in the literature with regard to the high frequency of non-attendance for price attributes (Campbell et al., 2012).

The papers described above all make use of de-briefing questions to identify and classify attribute non-attendance. This approach is described by Mariel et al. (2011) as Stated Non-Attendance (SNA), which they contrast with Inferred Non-Attendance (INA). The latter does not make use of de-briefing questions, but instead uses modelling approaches which search for patterns in the choice data which indicates non-attendance to attributes. Latent class models have been used by some authors in this way (Campbell et al., 2011; Hensher and Greene, 2010). The existence of an Inferred Non-Attendance approach begs the question of whether this is preferable to a Stated Non-Attendance approach. Mariel et al. (2011) use a simulation model to investigate the likely bias in welfare estimates produced by both SNA and INA. They find that, under certain conditions relating to serial versus choice task-specific attribute non-attendance, SNA produces unbiased welfare estimates, whilst INA does not. Importantly, in the INA the number of classes which are necessary to describe the attribute attendance pattern increase exponentially with the number of attributes, rendering the approach infeasible with more than 5–6 attributes[1] (Hensher, 2012). However, the SNA is also not free of problems. First of all, it relies on respondents' statements about attribute attendance, and as such involves extra cognitive costs for gathering this information. There may also be correlation between respondents' reported attendance and other modelling components that may induce an endogeneity bias, especially when the attendance is collected at choice task level. Hess et al. (2013) also caution against the interpretation of latent class models of attribute non-attendance using INA, which they show can over-state the implied extent of non-attendance considerably. They recommend an extended latent class approach where the distribution of preferences within one class is allowed to vary continuously, allowing both very low and higher preferences for an attribute to be represented; whilst pure non-attendance is picked-up in the other class. An alternative approach to modelling AN-A using a latent class approach is given by Hensher et al. (2012).

In this research, we opted for the SNA approach in a workshop context, where we elicit the attribute attendance at choice sequence level so as to reduce as much as possible the potential biases which may affect self-reporting. Moreover, the use of INA approaches was difficult in this case due to the large number of attributes.

3. Case Study

The case study used in this research was a choice experiment that aimed to determine the values people place on ecosystem services and biodiversity enhancements delivered by the UK Biodiversity Action Plan (BAP). This is a set of policy instruments that aim to conserve and enhance the UK's most important habitats and species. Given the complexity of the good to be valued, participatory workshops were used to carry out the survey (Alvarez-Farizo and Hanley, 2006; Christie et al., 2006; MacMillan et al., 2003). Each workshop group involved around 12 respondents, who met for around 2 h in a convenient public venue (e.g., museums). Participants were recruited from the local area on the day preceding the workshop, and were paid a small fee for attending the workshop. Around two-thirds of those who stated a commitment to attend the workshop, actually attended it: no significant differences were found in the key socio-economic characteristics of those who attended and those who did not.

The use of participatory workshops to collect the choice data allowed more time for the provision of information (including a specially-produced documentary film) on the complex relationship between BAPs, ecosystem services and economic values than would be available using other data collection formats, and promoted reflective learning amongst participants. Following this information provision, participants were asked to complete a series of five choice tasks,[2] where each task required respondents to select their preferred 'action plan' from a series of three plans: Action Plan A, Action Plan B and a Baseline Plan (see Fig. 1 for an example). Each Action Plan was described in terms of the effects on seven ecosystem service attributes (Wild food, Non-food products, Climate regulation, Water regulation, Sense of place,[3] Charismatic species and Non-charismatic species) and a monetary cost (Price) attribute. The services used were identified and defined through both public and expert focus groups and represented the services people could most readily understand. Participants completed these choice tasks individually, although they could discuss the choice problem with other workshop participants and the workshop moderators.

The levels of ecosystem service delivery in the Baseline Plan relate to a 'No further BAP funding' policy scenario in which the level of services declined, but at no additional cost to the respondent. The ecosystem service attributes in Plans A and B took one of three levels of delivery based on a 'Full policy implementation' scenario (where ecosystem service delivery increased), a 'Present BAP' scenario (where services were retained at current levels), and a 'No further BAP funding' scenario (where services declined). Detail of the levels of the ecosystem services delivered by the three UK BAP scenarios are summarised in Table 1 and are fully described in Christie et al. (2011). The monetary attribute in

[1] With k quantitative attributes, a 2^k rule for the combinations of attendance or non-attendance apply. For example with 4 attributes 16 possible combinations (classes) arise, whilst with the number of attributes used in this study 128 classes are required. This would be the minimum number by assuming homogeneous preferences amongst respondents who have attended the attribute. If preferences heterogeneity is considered and modelled discretely, the number of necessary classes would increase further; in the case of including it continuously for each random variable, it would be necessary to estimate a specific distribution, which is almost impossible with the typical sample size used in environmental valuation.

[2] In a workshop context presenting only five choice tasks to respondents may appear low. Louviere et al. (2011) pointed out that there may be both statistical and economic benefits by increasing the number of choice tasks answered by each respondent. However, in this experiment the choice experiment exercise was just a part of a long survey aimed to disclose respondent's knowledge about biodiversity services and their preferences towards it which brought us to reduce the number of choice task finally showed to respondents. In addition, biodiversity services are items not well known by respondents and required more time to be understood and effectively managed by respondents.

[3] The term 'Sense of place' was used to capture the 'cultural' services (such as the aesthetic, spiritual, educational and recreational benefits) delivered through the distinctiveness of landscapes; where that distinctiveness is influenced by the area and quality of individual habitats.

	Action Plan A	Action Plan B	BASELINE
Wild food	MORE WILD FOOD *14% more wild food in the UK*	LESS WILD FOOD *16% less wild food in the UK*	LESS WILD FOOD *16% less wild food in the UK*
Non-food products	MORE NON-FOOD *14% more non food products in the UK*	NO CHANGE *No change to non food products in the UK*	LESS NON-FOOD *16% less non food products in the UK*
Climate regulation	MORE CO_2 *Habitats release 749,000 tonnes CO_2 (3.12%) which contributes to global warming*	NO CHANGE TO CO_2	MORE CO_2 *Habitats release 749,000 tonnes CO_2 (3.12%) which contributes to global warming*
Water regulation	LESS FLOODING *67,000 fewer people at risk*	NO CHANGE *4,800,000 people at risk*	MORE FLOODING *69,000 more people at risk*
Sense of place	FEWER HABITATS MAINTAINED *28% of semi-natural and natural habitats maintained*	NO CHANGE *37% of semi-natural and natural habitats maintained*	FEWER HABITATS MAINTAINED *28% of semi-natural and natural habitats maintained*
Charismatic species	FEWER SPECIES MAINTAINED *0 species stabilised 273 species decline*	NO CHANGE *105 species stabilised 168 species decline*	FEWER SPECIES MAINTAINED *0 species stabilised 273 species decline*
Non-charismatic species	NO CHANGE 337 species stabilised 539 species decline	FEWER SPECIES MAINTAINED 0 species stabilised 876 species decline	FEWER SPECIES MAINTAINED 0 species stabilised 876 species decline
Cost per household (per year for 10 years)	£100 per year (Total =£1000 over 10 years)	£25 per year (Total =£250 over 10 years)	£0 per year

Fig. 1. Example of a choice experiment choice task.

the CE was specified as an annual increase in taxation over the next 10 years, in which the tax amount took one of six levels.

The attribute levels were allocated to choice tasks using a 'shifted' experimental design (Ferrini and Scarpa, 2007). In this design the choice cards are created by pairing two sets of orthogonal experimental designs and by shifting the levels of the second set. The D-efficiency of initial pairing of options is calculated and used as baseline from which the D-efficiency of subsequent shifted designs can be tested. The initial design of seven attributes plus cost (Price) attribute returned a D-efficiency value of 0.1659. The shifted design returns a D-error of 0.0203. An efficient design typically improves the statistical efficiency by maximising the mean distance between all attributes, therefore obtaining the maximum information from the minimum number of tasks. However, this comes at a cost that the experimental design may also have an impact on AN-A, given that maximising the difference amongst the attribute level in each choice set may induce a more difficult choice situation, which in turn may induce respondents to use heuristics to simplify it.[4] In addition to statistically efficiency, the final design was scrutinised so that to avoid unrealistic pairs or dominated options. Following the choice tasks, respondents were asked to indicate

[4] We thank an anonymous referee for pointing this out. A recent review on the core issues about experimental design and its likely effect on model parameters can be found in the paper of Louviere et al. (2011).

Table 1
Summary of the levels of the ecosystem service attributes used in the choice experiment.

	Full implementation	Present BAP	No further BAP funding
Wild food	14%	–	−16%
Change in availability of wild food (%)			
Non-food products	14%	–	−16%
Change in availability of wild food (%)			
Climate change	708	–	−749
Annual changes in CO_2 sequestration ('000 tonnes CO_2 yr^{-1})			
Water regulation	−67	–	+69
Change in no. of people at risk ('000 people)			
Sense of place	41.3	37.3	27.6
Habitat achieving condition (%)			
Charismatic species	273	105	0
Status of species	0	168	273
(No. of species stabilised)			
(No. of species declined)			
Non-charismatic species	876	337	0
Status of species	0	539	876
(no. of species stabilised)			
(no. of species declined)			

whether they 'always considered', 'sometimes considered' or 'never considered' each of the CE attributes when they made their choices. The responses to this question form the basis of much of the analysis reported in this paper.

Day et al. (2012) also argue that the design of the survey may also have an impact on AN-A. In particular, they argue that a stepwise disclosure format (where the respondent completes a series of unannounced choice tasks) is more prone to problems than advance disclosure format (in which respondents are made aware of the full set of choice tasks before the commencement of the exercise). Through the workshop setting, our respondents were made not only made aware of all five choice tasks, but also provided with an opportunity to go back and revise tasks at the end of the exercise. Thus, we are confident that the impact of the design on AN-A was minimal.

A total of 618 people were interviewed during 54 valuation workshops across the whole of the UK. From these, we removed the protest responses and the ones where people refused to trade-off biodiversity ecosystem services, obtaining a total of 441 respondents to use in the analysis. Our sample was found to be generally representative of that of the UK National Census; the exception was that our sample included a higher proportion of people that had attained a higher education qualification than that of the national average.

4. Methodology

The model chosen for the parametric analysis of responses is a mixed logit, an approach which has grown rapidly in popularity with discrete choice modellers. Mixed logit provides a flexible econometric method which may be used to approximate any discrete choice model derived from random utility maximisation (McFadden and Train, 2000).[5] Under the mixed logit approach the utility of respondent n from alternative j in choice situation t can be described as:

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt} \tag{1}$$

where X_{njt} is a vector of observed attributes for the good in question, β_n is the vector of coefficients for respondent n associated with these attributes, and ε_{njt} is an unobserved random term which is independent of the other terms in the equation, and independently and identically Gumbel distributed. The probability of individual n's observed sequence of choices $[y_1, y_2, \ldots y_T]$ is calculated by solving the integral[6]:

$$P_{n[y1,y2,\ldots,yT]} = \int \ldots \int \prod_t^T \left[\frac{e^{X_{njt}\beta_n}}{\sum_{i=1}^J e^{X_{nit}\beta_n}} \right] f(\beta_n) d\beta_n \tag{2}$$

where j is the alternative chosen in choice occasion t. The above integral has no analytical solution but can be approximated by simulation. To estimate the model, the analyst must make assumptions about how the β coefficients are distributed over the population. In this case, we assumed that all the non-monetary attributes are distributed following a triangular distribution. The parameter for the cost attribute was not allowed to vary across respondents, to facilitate the estimation of the WTP measures and to guarantee the existence of the WTP distribution (Daly et al., 2012).[7]

To evaluate the impacts of attribute attendance, the probability of choice must be conditioned to the situations of full attendance, partial attendance and no attendance to each attribute. To do that, the probabilities of choices are constructed in such a way that for those individuals who attended all the attributes the k elements of β_n that enter in the likelihood function are β_{nkac}; for those individuals who attended only sometimes to a given attribute the elements of β_n that enter in the likelihood function are β_{nksc}; and for those individuals who stated that they ignore a given attribute the elements of β_n that enter in the likelihood are β_{nknc}. We are thus partitioning the values of β_n, entering in the likelihood function as follows:

$$\beta_n = \left\{ \begin{array}{l} \beta_{nkac} \text{if respondent } n \text{ declared that always considered the } k\text{th attribute} \\ \beta_{nksc} \text{if respondent } n \text{ declared that only sometimes considered the } k\text{th attribute} \\ \beta_{nknc} \text{if respondent } n \text{ declared that never considered the } k\text{th attribute} \end{array} \right\}.$$

This re-parameterisation of the β_n is simply accommodated into the probability of choice by considering that each subset of coefficient has its own distribution, such that the probability of the sequence of choice for respondent n becomes:

$$P_{n[y1,y2,\ldots,yT]} = \int \cdots \int \prod_t^T \left[\frac{e^{Y_{nkac}X_{njt}\beta_{nkac}}}{\sum_{i=1}^J e^{Y_{nkac}X_{nit}\beta_{nkac}}} * \frac{e^{Y_{nksc}X_{njt}\beta_{nksc}}}{\sum_{i=1}^J e^{Y_{nksc}X_{nit}\beta_{nksc}}} * \frac{e^{Y_{nknc}X_{njt}\beta_{nknc}}}{\sum_{i=1}^J e^{Y_{nknc}X_{nit}\beta_{nknc}}} \right] \times \tag{3}$$

where Y_{nkac}, Y_{nksc}, and Y_{nknc} are indicator variables which assume the value of 1 when respondent n said that she 'always considered', 'sometimes considered' or 'never considered' the attribute k, and zero otherwise.

Previous approaches in the literature either restrict the coefficients of the non-attended attributes to zero (e.g., Campbell et al., 2008; Hensher et al., 2005) or estimate different coefficients for the attended and non-attended attributes (Campbell and Lorrimer, 2009). In the first case, the

[5] As an anonymous referee pointed out mixed logit may be inadequate statistically if not generalized to take scale differences into account. However, in the specific case study analysed in this article, the welfare measures obtained from a Generalized Multinomial Logit model (Fiebig et al., 2010) practically mirror those obtained from a simpler mixed logit model, a result already observed by Hensher and Greene (2010). We therefore opted for the use of simpler mixed logit in the analysis.

[6] This specification assumes that the person's taste, as represented by β_n, is the same for all choice situations.

[7] In analysis not shown in this paper we estimated models where we allow the price attribute to vary randomly following a bounded triangular distribution. Results showed the existence of heterogeneous preferences towards the price in the 'always considered' group and in the 'sometimes considered' group. Model fitting is better in some models and not statistically different in others. However, letting the price parameter vary amongst respondent does not affect our conclusions on attribute attendance. As such, we opted for keeping the price constant to ease the estimation of WTP.

non-attended attributes do not contribute to the likelihood function, so that the analyst implicitly assumes that these attributes are not relevant to respondents. Although this may be true when indeed the ignored attributes are not relevant to respondents, there is evidence that respondents may commit errors in self-stated responses and say that they ignore an attribute when in fact they did not (Carlsson, 2010; Hess and Hensher, 2010). In this second case, the non-attended attributes are left in the likelihood function and their utility parameters are separately estimated. As pointed out by Campbell and Lorrimer (2009), this approach provides a convenient method for assessing the accuracy of self-stated attribute processing responses.

To demonstrate the impact of attribute processing strategies on valuation we estimate and compare seven different models (see Table 2 for a summary of the strategies used in the models). Model 1 represents the standard approach in CE which does not account for attribute attendance, i.e., all choices are fully considered in the model. Models 2, 3, 4 and 5 follow the approaches used so far in the literature to address attribute non-attendance. In these models, we assume that we do not have information about the 'sometimes considered' case but only the two extreme 'always considered' and 'never considered' cases. Model 2 is specified by assuming all the 'sometimes considered' attributes are non-attended and is estimated by constraining the coefficients for these attributes equal to zero, i.e., assuming a marginal utility from this attribute equal to zero. Model 3 is a variation on Model 2, where the 'sometimes considered' attributes are assumed to be fully attended and only the parameters of the 'never considered' attributes are constrained to zero. Model 4 again assumes the 'sometimes considered' attributes as attended attributes but is estimated without placing any restrictions on the parameters for these attributes. Model 5 differs from Model 4 by assuming the 'sometimes considered' attribute as 'never considered' and allowing a free estimation for the coefficients of this group.

It is important to keep in mind that in these models we reconstruct the attendance analysis by assuming that the 'sometimes considered' attributes may fall either into the 'always considered' group or 'never considered' group. This is a strong assumption used for demonstrative purposes, given that for each of the 'sometimes considered' attributes we do not know the share which would have fallen into the 'always considered' and 'never considered' group if this would have been asked to respondents.

In Models 6 and 7, we thus explicitly utilise our data on 'sometimes considered' responses to represent partial attendance. Model 6 assumes that respondents ignore attributes when they do not affect their utility. Thus, in Model 6, we estimate separate parameters for fully attended (always considered) and partially attended (sometimes considered) attributes, but constrain non-attended (never considered) attributes to equal zero. Model 7 again explicitly accounts for partial attendance, but this time the analysis estimates separate parameters for the fully attended, partially attended and non-attended attributes.

The seven models outlined above allow us to address a number of questions relating to respondent's attendance in choice experiments, and approaches to accounting for non-attendance.

1. *To what extent do respondents attend to all of the attributes included in a choice experiment*? This question will be addressed by examining the frequency to which respondents 'always consider', 'sometimes consider' and 'never consider' attributes in this choice experiment.
2. *What is the impact of alternative strategies for dealing with attribute non-attendance*? To address this question we compare the standard CE approach that does not account for non-attendance (Model 1) with all other models which adopt alternative approaches to accounting for attribute non-attendance.
3. *Can respondents self-report non-attendance*? Following Carlsson et al. (2010), we compare models where non-attended attributes are constrained to zero (Models 2, 3 and 6) with models where non-attended attributes are estimated (Models 4, 5 and 7).
4. *Do respondents partially attend to attributes, and what are the implications of this*?
   There is evidence that respondents may attend to an attribute in some but not all choice tasks. In our study, we included an option where respondents could specify that they 'sometimes considered' an attribute. In Models 6 and 7, we explicitly specify partially attended attributes, testing both the significance and size of the relevant coefficients.

5. Results

In this section, we address each of the four questions highlighted above, and then explore the impacts of the different strategies on welfare measures.

5.1. To What Extent Do Respondents Attend to Attributes in Choice Experiments?

In our study, respondents were asked to state whether they 'always considered', 'sometimes considered' or 'never considered' the choice set attributes. Table 3 reports the frequencies of attendance for each attribute as declared by respondents.

The frequency of attribute attendance varies greatly across the attributes (Table 3). Respondents were most likely to 'always consider' the protection of Charismatic species (63% of respondents), Non-charismatic species (62%) and Climate regulation (58%). Only 34% of respondents stated that they 'always consider' Price, whilst Wild food and Non-food products were 'always considered' in 27% and 16% of cases. The frequencies of the non-attendance found in this study are lower than those reported in the literature: the highest level of non-attendance was found for the Wild food attribute in which 15% of respondents stating that they 'never considered' this attribute. The low levels of non-attendance in this study is largely due to the fact that we separately identify respondents who 'never considered' an attribute from those who 'sometimes considered' an attribute, but may also be due to the valuation workshop context in which choice responses were elicited.

The 'sometimes considered' case was the most frequent response for five of the eight attributes. Scarpa et al. (2010) and Meyerhoff and Liebe (2009) ask respondents to state whether they attended attributes after each choice task, which we argue is likely to be more cognitively challenging for the respondent, requires additional costs in term of survey time. Moreover, if the analyst assumes that a non-attended attribute does not affect the respondents' utility, then it can also be assumed that this attribute should not affect utility in any of the choices. Indeed, the existence of attribute non-attendance at the choice task level reveals that respondents have a low sensitivity for an attribute and confound this low

Table 2
Approaches used to model attribute attendance.

Original attendance response	Approach used to model attribute attendance						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Always considered	Fully attended	Fully attended	Fully attended	Fully attended	Fully attended	Fully attended	Fully attended
Sometimes considered	Fully attended	Constrained $\beta = 0$	Fully attended	Fully attended	Not attended	Partially attended	Partially attended
Never considered	Fully attended	Constrained $\beta = 0$	Constrained $\beta = 0$	Not attended	Not attended	Constrained $\beta = 0$	Not attended

Table 3
Respondents' self-reported attribute attendance.

Attribute	Always considered (%)	Sometimes considered (%)	Never considered (%)
Wild food	27.2	65.8	7.0
Non-food products	16.6	67.8	15.6
Climate regulation	58.5	39.2	2.3
Water regulation	43.8	51.5	4.8
Sense of place	34.5	55.8	9.8
Charismatic species	63.0	35.1	1.8
Non-charismatic species	61.9	33.8	4.3
Price	34.0	57.4	8.6

sensitivity with non-attendance (Hess et al., 2013). Behaviourally, this may happen when the attribute value is below a respondent threshold level[8] or when the attribute level becomes significant to respondent because it is in conjunction with another attribute (an interaction effect). Our approach was instead to ask respondents questions on attribute attendance after all choices had been made, in which we included a 'sometimes considered' option to identify partial attendance as a category which can include multiple reasons for attribute non-attendance by respondents. We argue that our approach is cognitively easier. We test later in this paper as to whether this approach is capable of deriving robust and behaviourally meaningful value estimates.

Attribute non-attendance may also be influenced by the experimental design. A shifted design increases the differences amongst the attributes in a specific choice card and thus result in more difficult choices, which in turn may lead to increas the use of heuristics by respondents. In the specific case of this study we are confident that this did not happen because the experiment was carried out in a workshop setting, where respondents had plenty of time to think about the attributes and attribute levels presented in the choice cards. In addition, they could raise and clarify with the moderator all the doubts regarding the attributes and attribute levels used. Furthermore, in addition to attribute attendance, we asked respondents about the importance to them of the ecosystem services used in the design. The analysis of the correlation between the attribute attendance and the importance respondents assigned to the ecosystem services reveal a very large correlation, which is statistically significant at the 99.9% confidence level. As such, we can conclude that when respondents declared either to have partially attended or not attended an attribute it was not because of an experimental design effect, but because his/her marginal utility from the attribute was lower or zero regarding this attribute.

5.2. What is the Impact of Alternative Strategies to Dealing with Attribute Non-attendance?

A series of models were estimated to investigate the impact of alternative strategies for accounting to non-attendance. A total sample of 2205 choice observations was used for model estimation. Table 4 reports the coefficients for the seven models investigated.[9]

In Model 1 (which represents a standard CE model that does not account for attribute attendance), most parameters that were 'always considered' are significant at the 95% level or higher and have the expected signs: the exceptions are the Wild Food and Non-Food Product attributes. These results reveal that respondents have positive values for most of the ecosystem services delivered by the UK BAP, but that they are not interested in the effect of the plans on Wild Food and Non-Food Products. The positive and significant values of the alternative specific constant (ASC) show that respondents had a propensity to choose any policy option over the status quo option. The fit of this basic model is decent with an adjusted rho^2 value of 0.315.

In Models 2, 3, 4 and 5, we assume that we do not have information on partial attendance, but only on 'always' or 'never' attending, and model the four alternative approaches to accounting for attribute non-attendance listed in Table 3. In Model 2, we only estimated parameters for responses that are fully attended. Attributes that were 'sometimes considered' or 'never considered' are assume to be non-attended and their parameters are restricted to zero. Although all the ecosystem service attributes are significant in this restricted model, this model had the lowest explanatory power: LogL $= 1765$, and adjusted rho$^2 = 0.27$. As may be expected, treating the large share of responses that were partially attended as being not attended, and in addition assuming that all these attributes do not have any effect on utility, leads to a reduction of the statistical power of the model.

In Model 3, we join the 'sometimes considered' group to the 'always considered' and model these combined responses as fully attended, maintaining the parameters of the 'not considered' attributes equal to zero. Model 3 is statistically superior to the previous models indicating that it is better to assume the parameters of the 'never considered' attribute equal zero, and that the preferences for the 'sometimes considered' attributes are more similar to the 'always considered' than to 'never considered' ones.

Model 4 is similar in spirit to Model 3 although it allows a free estimation of the parameter for the ignored (never considered) attributes. It is interesting that none of the parameters for the never considered attributes are statistically different from zero revealing that indeed people who declared that they ignored an attribute did not derive utility from it. This model is statistically superior to all the previous models but Model 3,[10] due to the extra degrees of freedom necessary for estimating the set of coefficients for the ignored attributes.

Similar to Model 2, Model 5 treats the 'sometimes considered' responses as non-attended. However, Model 5 is specified to estimate coefficients for both full attendance and non-attendance (where the latter comprises the 'sometimes considered' and 'never considered' cases). The important finding here is that the coefficients of the non-attended attributes are mostly significant. This indicates that the group of people who state that they sometimes or never considered the attributes still derived utility from these attributes, albeit at a lower level of utility than those in the fully attended group. However, statistically this model is inferior to all the previous models (save Model 2), indicating that it is not beneficial to join the 'sometimes considered' attributes with 'never considered' responses.

5.3. Can Respondents Accurately Self-report Non-attendance?

Following Carlsson et al. (2010), we test whether respondents can accurately self-report attendance by comparing Models 3, 4 and 5. When we disentangle the effect of the 'sometimes considered' attribute from the 'never considered' group (Models 3 and 4), we find that respondents can indeed accurately self-report attribute attendance. If we treat respondents who 'sometimes considered' an attribute as if they have ignored it, then one derives the erroneous result that people cannot accurately self-report attribute attendance. This suggests that the main issue in tracing non-attendance is not whether people can accurately state this, but rather how researchers choose to measure it. When we assume that the analyst would have elicited the attribute

[8] This is the case when, for instance, all the alternatives in the choice cards shows a price which is below the respondent's willingness to pay for the changes illustrated in the choice card. In this case, the respondent does not focus his/her attention on the price attribute, but on the other attributes and believing that he ignored the price, states not to have considered it. This is clearly wrong, given that indeed he considered the price, although it was not determinant for the choice he made in this specific choice set.

[9] For the sake of space, we do not report the standard deviations of the random parameters. Briefly, we can say that there exists a degree of heterogeneity in respondent's preferences for all attributes save the Non-charismatic species attribute, and that the degree of heterogeneity decreases when the attribute attendance analysis is considered. Full model results are available from authors upon request.

[10] A comparison of model fit cannot be carried out using conventional log likelihood ratio tests because models are non-nested. Hence, we use the test proposed by Ben-Akiva and Swait (1986) for non-nested choice models.

Table 4
Model coefficients and statistics.

Variable	Model 1	Model 2	Model 3[a]	Model 4[a]	Model 5[b]	Model 6	Model 7
'Always considered'							
ASC	1.740*	1.89	1.770*	1.727*	1.787*	1.780*	1.837*
Wild food	0.056	0.010*	0.04	0.053	0.043	0.038	0.046
Non-food products	0.004	0.15*	0.025	0.019	0.14	0.150*	0.13
Climate regulation	0.025*	0.02*	0.025*	0.026*	0.026*	0.028*	0.027*
Water regulation	−0.006*	−0.0004*	−0.006*	−0.006*	−0.006*	−0.006*	−0.007*
Sense of place	0.235*	0.228*	0.205*	0.223*	0.357*	0.337*	0.401*
Charismatic species	0.064*	0.051*	0.058*	0.060*	0.063*	0.062*	0.065*
Non-charismatic species	0.016*	0.010*	0.016*	0.017*	0.018*	0.018*	0.020*
Price	−0.062*	−0.061*	−0.066*	−0.067*	−0.076*	−0.074*	−0.081*
Sometimes considered							
Wild food						0.043	0.064
Non-food products						−0.014	−0.029
Climate regulation						0.021*	0.020*
Water regulation						−0.005*	−0.006*
Sense of place						0.123*	0.145*
Charismatic species						0.046*	0.045*
Non-charismatic species						0.011*	0.015*
Price						−0.064*	−0.068*
Never considered							
Wild food				0.103	0.066		0.206
Non-food products				−0.061	−0.036		−0.092
Climate regulation				−0.019	0.017		−0.044
Water regulation				−0.001	−.005*		−0.001
Sense of place				0.141	0.144*		0.19
Charismatic species				0.052	0.044*		0.05
Non-charismatic species				0.007	0.010*		0.009
Price				0.0004	−.055*		−0.001
Model statistics							
N (observations)	2205	2205	2205	2205	2205	2205	2205
Log likelihood	−1653.9	−1765.1	−1643.5	−1639.2	−1643	−1633.6	−1615.5
McFadden adjusted ρ^2	0.315	0.269	0.319	0.32	0.317	0.321	0.326
χ^2	1536.9*	1314.6	1557.8*	1566.4*	1588.8*	1577.7*	1613.9*

Notes:
* Denote significance at the 95% level or superior.
[a] The always considered coefficients represent the always considered and sometimes considered group.
[b] The never considered coefficients represent the sometimes considered and never considered group.

attendance in a dichotomous way, i.e., by assuming either that the 'sometimes considered' attribute are fully attended or not attended, we can conclude that the best model is obtained when the 'sometimes considered' attribute is treated as 'always considered', if at the same time we assume the parameters of the 'not considered' attribute are equal to zero (Model 3). Any other treatment reduces the statistical performance of the model. Thus, it seems to be important to distinguish between a low degree of attention being paid to an attribute in some choice situations with paying no attention (Hess et al., 2013). Random parameter modelling of the joint set of 'always' and 'sometimes' considered responses for a given attribute allows for this variation in the degree of attention being paid to that attribute in different choice situations.

5.4. Do Respondents Partially Attend Attributes and What are the Implications of This?

Unlike the previous four models, Models 6 and 7 explicitly account for partial attendance. In Model 6, we included those responses where individuals declared that they 'always considered' (full attendance) or 'sometimes considered' (partial attendance), whilst the parameters of 'never considered' responses (non-attendance) were restricted to zero for each person. Model 6 thus fully describes the respondent's statements about the attribute attendance, because its specification exactly follows what respondents declared. The values of the coefficients estimated for the 'sometimes considered' case are always lower than the values for the 'always considered' case, thus showing that people who only 'sometimes consider' an attribute have a lower marginal utility for these ecosystem services, indicating a lower sensitivity towards changes in the values they take. This model is statistically superior to all the previous models, showing the importance of explicitly considering the 'sometimes consider' responses in addition to the always and never categories.

In Model 7, we use the same model specification as in Model 6 but we freely estimate the parameters of the 'never considered' attributes rather than restricting them to be zero. This allows us to determine to what extent respondents made their choice consistently to what they stated regarding attribute attendance. Very interesting results emerge. First, all the significant coefficients in Model 6 for the 'always considered' and 'sometimes considered' attributes are still significant with the same signs. Second, the diminishing of the marginal utility of each attribute is still observed for the 'sometimes considered' case relative to the 'always considered' case. Third, and importantly, all the coefficients for the 'never considered' attributes are not significantly different from zero. This result differs from what has been found in other studies. For instance, Campbell and Lorimer (2009), Carlsson et al. (2010) and Hess and Hensher (2010) find significant coefficients for many attributes that respondents declared to have ignored. In the light of our results, we attribute this behaviour not to errors in respondent's stated attendance but to the design of the debriefing questions on attendance. The high frequencies observed in our study for the 'sometimes considered' case confirms the existence of partial attendance (Table 3). A design which allows identification of partial attendance is desirable as it may help to avoid self reporting errors.

6. Welfare Impacts

Above, we explored the effects of attribute attendance on the modelling of respondent's preferences. We now explore the impacts

Table 5
Attribute marginal WTP (£) and 95% confidence intervals.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Wild food	NDF 0	NDF 0	NDF 0	NDF 0	NDF 0	NDF 0	NDF 0
Non-food products	NDF 0	0.19 (0.05 0.34)	NDF 0	NDF 0	NDF 0	NDF 0	NDF 0
Climate regulation	0.41 (0.24 0.59)	0.06 (0.03 0.08)	0.28 (0.13 0.45)	0.29 (0.22 0.35)	0.28 (0.18 0.38)	0.28 (0.19 0.37)	0.25 (0.17 0.33)
Water regulation	−0.09 (−0.12 −0.06)	−0.01 (−0.00 −0.02)	−0.06 (−0.09 −0.04)	−0.06 (−0.07 −0.05)	−0.07 (−0.09 −0.05)	−0.06 (−0.08 −0.05)	−0.07 (−0.08 −0.05)
Sense of place	3.83 (2.26 5.48)	0.36 (0.18 0.58)	1.97 (0.75 3.20)	2.35 (1.77 3.00)	2.43 (1.61 3.33)	1.97 (1.28 2.69)	2.19 (1.49 2.97)
Charismatic species	0.99 (0.76 1.27)	0.12 (0.08 0.17)	0.64 (0.41 0.89)	0.67 (0.58 0.77)	0.70 (0.55 0.87)	0.64 (0.51 0.76)	0.61 (0.48 0.75)
Non-charismatic species	0.26 (0.17 0.36)	0.02 (0.01 0.04)	0.17 (0.08 0.26)	0.18 (0.15 0.22)	0.19 (0.14 0.25)	0.17 (0.12 0.22)	0.19 (0.14 0.24)

Note: NDF means Not Different From 0 at the 95% level.

of attribute attendance on welfare estimates for changes in ecosystem service attributes.

Before describing these WTP results, it is worth restating the assumptions made for their estimation. In the case of Model 1, we simply divide the marginal utility of a specific attribute by the marginal utility of income. In Models 2 and 3, we use the same formula but we assume that WTP = 0 in all cases where an attribute was not attended to. In Model 4, we estimated separate coefficients for respondents who 'always considered', 'sometimes considered' and 'never considered' an attribute. This leads to four alternatives for WTP estimation: when both the attribute in question and the price are 'always' or 'sometimes' considered ($WTP_1 = \beta_{asc} / \beta_{asc\text{-}price}$); when the attribute is 'always' or 'sometimes' considered, but price is not ($WTP_2 = \beta_{asc} / \beta_{nc\text{-}price}$); when the attribute of interest is 'never considered', but price is ($WTP_3 = \beta_{nc} / \beta_{asc\text{-}price}$); and when neither the attribute nor the price is considered ($WTP_4 = \beta_{nc} / \beta_{nc\text{-}price}$). However, given that all the estimated attribute preference parameters for the not-considered group are statistically not different from zero, we constrained the WTP for these respondents to zero. Strictly speaking we could not estimate the WTP for respondents who have a zero coefficient for the price attribute, given we do not have an estimate of their marginal utility of income.[11] However, we assume these respondents to have a zero WTP.[12] The resulting WTP is thus the sum of these four WTP alternatives, weighted according to its frequency. The same is done in Model 5 with the difference that the two groups of interest are 'always considered' and 'sometimes considered' or 'never considered'. Note that the WTP has been calculated for all significant parameters in this case.

In Models 6 and 7, a similar process was followed. However, in these models we also needed to consider the effect of 'sometimes considered' for attribute and for price in the WTP estimation. So WTP estimates also include: $WTP_5 = \beta_{ac} / \beta_{sc\text{-}price}$; $WTP_6 = \beta_{sc} / \beta_{ac\text{-}price}$; $WTP_7 = \beta_{sc} / \beta_{sc\text{-}price}$; $WTP_8 = \beta_{nc} / \beta_{sc\text{-}price}$; and $WTP_9 = \beta_{nc} / \beta_{sc\text{-}price}$. As in Model 4, respondents who declared they have 'never considered' a certain attribute were assigned a WTP equal to zero. Table 5 reports the marginal WTP estimated using the mean coefficient values shown in Table 4, along with the 95% confidence intervals calculated by mean of bootstrapping (Krinsky and Robbs, 1986). Focusing on the significant attributes only, WTP values are highest in Model 1 (where all responses were considered in the model) and lowest for Model 2 (where we constrained the coefficients of the 'sometimes considered' and 'never considered' attributes to equal zero). The WTP amounts for Models 3–6 (which account for attribute attendance) are quite similar and generally lie in between the WTP estimates of Models 1 and 2.

We formally test for differences in WTP amounts between models using the Poe et al. (2005) test (Table 6). As expected, we find that WTP amounts for attributes in Model 1 are significantly higher than in Model 2. The reason for this is that the 'sometimes considered' and 'never considered' attributes were constrained to zero in Model 2. Further, all of the WTP measures from Models 1 and 2 are significantly different from those in the models that account for attribute attendance (Models 3–7), showing the importance of properly measuring the extent to which people attend to attributes. No significant differences are observed for the WTP measures estimated in all other models. The similarity between the welfare measures of Models 3 and 4, and Models 6 and 7 were expected: the coefficients for the 'never considered' attributes in Models 4 and 7 are not different from zero (Table 6), whilst those in Models 3 and 6 were restricted to equal zero. The similarity between the welfare measures of these models and Model 5 is because the coefficients of the group formed by the 'sometimes and never considered' in Model 5 represent the 'weighted mixture' between the preferences of the sometimes and never considered groups where the latter has only a marginal effect due to the low percentage of respondents who declared to have never attended an attribute. As can be seen, this effect reduces slightly the values of the coefficients relative to the ones estimated for the 'sometimes considered' group in Models 6 and 7.

Thus, consideration of attribute attendance has a big impact on estimates of respondent's preferences and on WTP measures. However, what this impact is depends on the assumptions which are made when modelling attribute attendance. If we assume that the welfare measures of Model 7 are the most accurate, results indicate that it does not matter whether the analyst constrains parameters of the people who declared to have 'never considered' some attribute to zero. Also it does not matter, on a WTP basis, whether the analyst treats the 'sometimes considered' group as though they have the same preferences of either the 'always considered' or 'never considered' group, so long as one attaches a zero utility to people who ignored the attributes in the first case and allows a free estimation of parameter in the second case.

7. Conclusions

This paper looks at the issue of whether respondents consider trade-offs between all attributes used in a choice experiment design, and the implications of different ways of monitoring attribute non-attendance. We introduce an intermediate case of 'sometimes considering' an attribute, in addition to 'always' or 'never' considering this characteristic of the choice set. The use of this intermediate case of 'sometimes considered' for attributes turns out to be useful for better describing respondents' preferences. The fact that respondents declared that they only attended to a particular attribute sometimes, and that this statement is

[11] As pointed out by Carlsson et al. (2010) these respondents are a rather special case. The zero disutility of the price can be attributed to a protest against making a trade off between money and the environment, or to an extreme yea-saying. As such, considering the WTP of this group = 0 is a conservative estimation of the mean WTP for the total sample.

[12] This is a conservative way of treating the responses of respondents who declared to have ignored the price attribute, given that an alternative assumption may be to consider that those who ignored the price have the same mean marginal utility of income as those who did not.

Table 6
Poe et al. (2005) test results.

	Wild food	Non-food products	Climate regulation	Water regulation	Sense of place	Charismatic species	Non-charismatic species
Model 1 vs. Model 2	NA	NA	**1.00**	**0.00**	**1.00**	**1.00**	**1.00**
Model 1 vs. Model 3	NA	NA	**0.93**	**0.03**	**0.97**	**1.00**	**0.95**
Model 1 vs. Model 4	NA	NA	**0.91**	**0.03**	**0.96**	**0.99**	**0.92**
Model 1 vs. Model 5	NA	NA	**0.90**	**0.09**	**0.94**	**0.98**	0.88
Model 1 vs. Model 6	NA	NA	**0.91**	**0.04**	**0.98**	**1.00**	**0.95**
Model 1 vs. Model 7	NA	NA	**0.95**	**0.07**	**0.97**	**1.00**	**0.90**
Model 2 vs. Model 3	NA	NA	**0.00**	**1.00**	**0.00**	**0.00**	**0.00**
Model 2 vs. Model 4	NA	NA	**0.00**	**1.00**	**0.00**	**0.00**	**0.00**
Model 2 vs. Model 5	NA	NA	**0.00**	**1.00**	**0.00**	**0.00**	**0.00**
Model 2 vs. Model 6	NA	NA	**0.00**	**1.00**	**0.00**	**0.00**	**0.00**
Model 2 vs. Model 7	NA	NA	**0.00**	**1.00**	**0.00**	**0.00**	**0.00**
Model 3 vs. Model 4	NA	NA	0.43	0.51	0.35	0.44	0.36
Model 3 vs. Model 5	NA	NA	0.51	0.24	0.67	0.67	0.67
Model 3 vs. Model 6	NA	NA	0.48	0.55	0.68	0.61	0.56
Model 3 vs. Model 7	NA	NA	0.67	0.67	0.50	0.73	0.33
Model 4 vs. Model 5	NA	NA	0.46	0.25	0.55	0.63	0.56
Model 4 vs. Model 6	NA	NA	0.46	0.45	0.21	0.34	0.32
Model 4 vs. Model 7	NA	NA	0.27	0.33	0.37	0.23	0.55
Model 5 vs. Model 6	NA	NA	0.50	0.69	0.20	0.26	0.30
Model 5 vs. Model 7	NA	NA	0.36	0.59	0.34	0.18	0.49
Model 6 vs. Model 7	NA	NA	0.66	0.61	0.34	0.61	0.30

Note: Bolded data denote a significance level at p-values lower than 0.10 or greater than 0.90 (i.e., reject the null hypothesis that WTPs or CSs are equivalent).

the one with the largest share of responses, reveals that allowing for this class of response is valuable.

We find that a model which explicitly models those who 'sometimes consider' an attribute is statistically superior to all models which do not do so, showing the importance of explicitly considering the 'sometimes considered' responses in addition to the 'always' and 'never' categories. Another important finding is that when we model the group of people who declared they have ignored an attribute independently from the other groups, all the attribute parameters are not different from zero. This result contrasts with previous results such as Carlsson et al. (2010). Carlsson et al. observed that when an individual declared that they did not attend to a particular attribute, it did not mean that the attribute's marginal utility is zero. Indeed this happens in our data when we fail to distinguish the 'sometimes considered' group from the 'never considered' group (Model 5). In the light of these results we highlight the importance of disentangling the effects of 'partial attendance' from those of 'full' or 'non'-attendance to better describe respondent's preferences. Relying on a measure of attribute attendance through a dichotomous question leads to erroneous conclusions due to the allocation of respondents who only sometimes consider an attribute into either the always or never considered group.

One possible reason for the mismatch between respondent's declarations on attribute attendance and their choices is that people ignore an attribute in some of their choices but consider them in others. This partial attendance may be due to respondents finding a specific attribute level unrealistic in some choice cards, because they want to reduce the cognitive burden of the choice in the most difficult cases, or because they use a disjunctive choice rule when the attribute level in question does not meet a minimum acceptable level. Our analysis extends the standard approaches to considering attribute attendance by incorporating partial attendance into the models. We argue that this approach is better for assessing the accuracy of the self-stated attribute processing strategy.

Asking respondents about their attribute attendance after each choice occasion (such as done by Meyerhoff and Liebe, 2009; Scarpa et al., 2010) may increase the burden of the choice task and would not always be a reasonable response to request, especially when valuing unfamiliar environmental goods and services. The use of the 'sometimes considered' case at the end of a choice sequence can be an alternative and easier approach to deal with the heterogeneous pattern of attribute attendance. Future research aimed to compare the approach presented here and the approach where the attendance is elicited after each choice may determine whether the two approaches provide similar results in term of preferences and aggregate welfare measures. Future research should also investigate the effect that the survey design may have in the attendance to alternatives, attributes or attribute levels.

The design followed in this study did not allow us to determine exactly the reasons which led respondents to attend a specific attribute only in some choice cards and not in others. A possible reason is that respondents consider attributes only when their level is over or below a specific threshold value (Bush et al., 2009). This also may explain the large 'partial' attendance to the tax attribute, which is the third most frequently 'sometimes considered' attribute. In this case, respondents who seem to have ignored an attribute simply because its value is below or above a specific amount are indeed considering the attribute albeit that they declare they are not.

Taken together, findings from the choice experiment literature suggest that the conventional economic model of respondents exercising fully rational choices by trading off across all attributes in their choice set may not be the best way of representing behaviour. However, an accurate way of measuring the extent to which people do or do not pay attention to attributes is needed to properly assess the impacts of apparent non-attention on economic welfare measures. We contend that the approach used here offers advantages over those previously employed, since it allows for the key difference of sometimes paying attention, compared to never paying attention. This finding is in accord with the recent innovations in latent class modelling of attribute non-attendance such as Hensher et al. (2012) and Hess et al. (2013), which also focus on the importance of this distinction.

Acknowledgements

We thank the UK Department of the Environment, Food and Rural Affairs for funding the empirical study on which this paper is based and the support of project RTA2009-00024-00-00 funded by the Spanish Institute for Agricultural Research INIA and co-funded by the FEDER fund.

Appendix A. Supplementary Data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ecolecon.2013.08.016.

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